Proceedings of the 2006 IEEE
International Conference on Control Applications
Munich, Germany, October 4-6, 2006

Predictive estimation of the road-tire friction coefficient

Frédéric Holzmann*, Mario Bellino†
Roland Siegwart* and Heiner Bubb‡

*Ecole Polytechnique Fédérale / Lab of Autonomous Systems - Lausanne, Switzerland
Email: {frederic.holzmann, roland.siegwart}@epfl.ch

†Ecole Polytechnique Fédérale / Lab of Microtechnical Production - Lausanne, Switzerland
Email: mario.bellino@epfl.ch

‡Technical University of Munich / Chair of Ergonomics - Munich, Germany
Email: bubb@lfe.mw.tum.de

***Abstract*— The road-tire friction coefficient μ is as fundamental information for the algorithms dealing with the vehicle dynamics with high accuracy like in emergency cases. This paper introduces a new predictive methodology for the estimation of μ by using a camera and a microphone. After a description of the limits of the current methodologies, the new concept will be described step-by-step by following the data flow. The algorithm extracts the patterns corresponding of the different μ depending on the general luminance. These patterns will be matched on the current specimens to deduce the friction coefficient along the road ahead and a confidence value. Finally the results will be auto-correlated over the time to improve their stability. Moreover the reliability will be improved over a correlation with local measures based on microphone.**

The estimation of the road-tire friction coefficient μ is fundamental for an adequate computation of the vehicle dynamics. Therefore different approaches have been investigated during the European SPARC project; and the method presented here has been chosen finally to be integrated on both truck and passenger car prototypes.

I. Needs of a new RTFE methology

Several methods to estimate μ are based on the vehicle state where internal sensors are used by an auxiliary function conjointly to a dynamic vehicle model. The actual state of the vehicle and the reaction to a motion command permit to find the limitation of the realization of the given command. The single link between the vehicle actuators and the road is the contact road - tire which means μ. Three different approaches based on this idea are already under investigations as [1] reported. Each approach focuses on a different level of the vehicle-road model to extract some laws about the road-tire friction.

A vehicle-based system [2] and a wheel-based system [3] determine the slip value and use a tire dynamic model to extract μ. The relation between the slip and the friction coefficient is extracted from the Pacejka magic formula, which needs to be calibrated specifically for the tires. The single difference between both methodologies is the way to determine the slip value. The vehicle-based method uses measures of vehicle lateral and longitudinal motion, and wheel-based approach extracts the torque transferred on the wheels from the powertrain.

The third method is based on measurement of tire deflections from piezoelectric strips embedded in the regular tires of the vehicle. The inherent problem of this method comes from the local measurement on the tires and cannot give continuous data. Furthermore, the integration of several special sensors and their wireless communication to the body shield implies high cost.

These three kinds of measurement are dealing with both road surface and tire. Therefore their accuracy can be relative good but can only provide reactive measures. In the next couple of years the assistant systems will have to deal wider with the environment. Therefore exterioceptive sensors will be needed to look at the μ coefficient in advance like camera or laser scanner.

Unfortunately, as they have no tire information, they can only deliver a worth case estimation. Therefore the predictive measurements are up to now depending on a calibration of the tires' model contrary to the reactive measurements, which could determine the characteristics of tires by themselves. With these predictive methods, 6 different classes of μ can be defined : (1) icy, (2) wet, (3) humid cobblestone, (4-6) from bad to excellent coefficient.

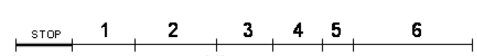


Fig. 1. Ranges of μ

II. Algorithms using a camera

A. Extraction of the ranges to analyze

Some investigations with camera have already been done like in Japan by Kuno and Sugiura [4]. But these tests are based only on detection of the road surface gloss, which is not the only one factor for the estimation of the friction coefficient. Here the approach will try to go step further with a grayscale camera.

The results of a lane detection like in [5] define the lateral limits of the range to analyze. In addition an algorithm for object detection defines the depth of the analysis range. No correction is needed to obtain a bird view like done in [6] because the picture will be split into several small areas like on figure 2 for local analysis with a low residual errors. To simplify the algorithms, a static height of 30 pixels is set for the different areas. This able to get maximally 9 areas to monitor on the (640x480) picture. If the areas are not wide enough, the results of the computation will not be stable enough as some important variation of luminance may appear during some instants.

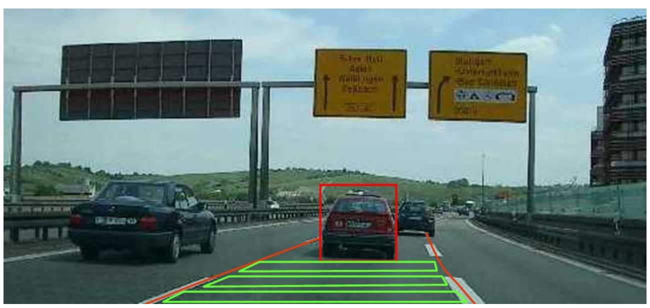


Fig. 2. Split of the range to monitor

B. Choice of the new methodology

The main idea is to determine for each range above the vehicle the type of condition: road surface, humidity, snow etc. Three different approaches are already possible to use for the analysis:

- Statistical approach: the luminance of the pixels and their repartition on histograms are analyzed to extract some properties.
- Macroscopic approach: the co-occurrence matrix is calculated to describe the amount of neighborhoods of the pixels and the energy of the luminance.
- Microscopical approach [7]: a 2D Fourier transformation is applied on the picture to model the irregularities of the road and the regular patterns.

As explained in [4], a robust use of the statistical approach needs a learning system. Due to the huge needs of computation capacity, it cannot be integrated now into embedded systems right now. The last approach based on the high frequencies of variation of road texture is quite difficult with the use of a camera, which is continuously vibrating due to the connection to the chassis of the vehicle.

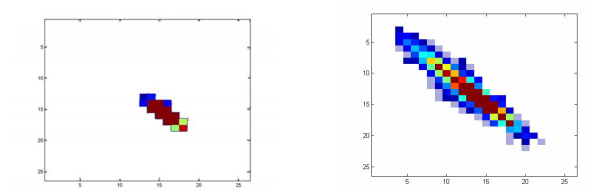
The macroscopic approach will be used here by integrating both texture analysis and gloss measurement. This approach will be partially similar as estimation of landscape characteristics based on snapshots taken by satellites like in [8], [9] or [10]. Some properties of this matrix like the global luminance, the energy or the variance can be used to characterize some types of textures.

The co-occurrence matrix from the different ranges will be calculated and hyperspheres will be matched on the characteristically forms of the matrix. Next the hyperspheres are compared to the different models for the current luminance. Finally the new graph of μ over the distance is fused with the other graphs computed over the time to enhance the reliability.

III. Predictive measures

A. Co-occurrence matrices

For a picture I with n levels of gray (here 50), its co-occurrence matrix M_I with the dimensions n x n will describe the amount of pair wise of pixel luminance on the picture. For each pixel $p_{i,j}$ with the index (i,j) and the luminance k, its likelihood with its right neighbor $q_{i,j+1}$ with a luminance l increases the value with the index (k, l) of the co-occurrence matrix. On the next figure, the co-occurrence matrices for a macadamized road and for cobblestones shown interesting differences. A summation of the pixels' level on the diagonal top left to bottom right is corresponding to the histogram of the picture. And a summation on the other diagonal describes the histogram of the picture derivate.



(a) Macademized road (b) Cobblestones

Fig. 3. Example of two co-occurrence matrices

The noticeable difference between both matrices can be used to estimate the type of texture. A 3D rendering of this matrix always looks like a Gaussian surface. Its maximum will be used as first characteristics because it corresponds to the global luminance. The width of the surface along the diagonal and the wise perpendicularly to it will be the two other characteristics. Here the height of the maximum will not been taken into account, even if it describes indirectly the homogeneity of the picture. But to accelerate the computation, Gaussian surfaces will not been used directly but only the definition of there ranges.

The form of these curves will be well defined for the road portions close to the vehicle as shown on figure 5, but the widest portions will get blurred matrices, because of the distance and the image correction. Therefore their matrices will tend to go to the white levels (bottom right) while good luminance or to the dark levels (up left) during night.

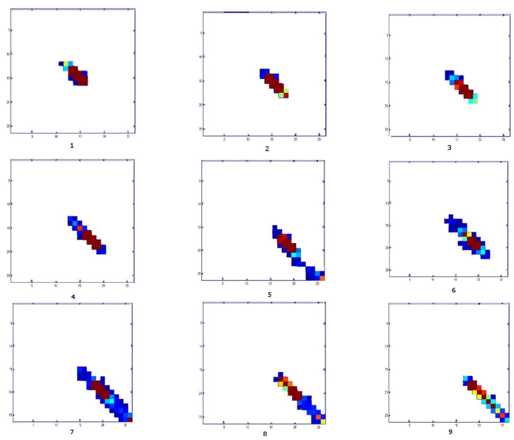


Fig. 4. Co-occurrence matrix for a macadamized road (μ = 0.65)

B. Online extraction of the patterns

Many measures have been performed on test tracks, where the friction coefficient has been estimated beforehand, with different conditions (dry, humid, wet) as on figure 5. The measures with snow have been done independently from the road texture because they are partially masked with the snow.

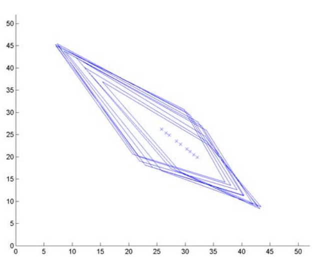
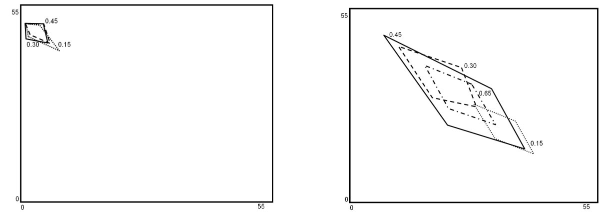


Fig. 5. Co-occurrence matrix for cobblestone roads (μ=0.45)

The measures have been matched together to define static models for several levels of luminance. The modification of the patterns over the luminance (or actually the position of the optimum) is quite linear between the two extremems shown on figure 6. With this approximation, the patterns can be extracted on-line by looking at the luminance. The position of the maximum of the co-occurrence matrix is searched on the diagonal and its distance to the two extreme weights there patterns.



(a) Night purpose (b) Maximal luminance

Fig. 6. Extreme patterns

C. Single determination of the graph of μ

Consequently a each time, for several areas to analyze there exists a rhombus to classify with different models. Each pattern has to be matched on the rhombus and the distances between the j extremities E_j are measured. Parallel to the generation of the patterns, the standard deviations have also been measured to determine the probabilities of appurtenance as Gaussian curves. The confidence values for the j extremities $E^{\star}_{i,j}$ can be extracted from these empirical curves and the fusion of these 4 inputs set the probabilities P_i of the i different classes of μ with the following equation.

$$P_i = \frac{\prod_j a_j \cdot P(E_{i,j})}{\prod_j a_j \cdot P(E_{i,j}) + \prod_j a_j \cdot \overline{P(E_{i,j})}} \qquad (1)$$

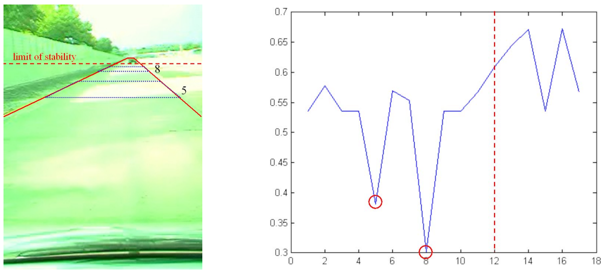
The a_j parameters weight the influence of each extremity. In practice, the extremities along the top left to bottom right diagonal have a higher weight because their wide range is easier to separate into different classes. The estimation of μ is calculated from the fusion of the different probabilities by using the next equation. The final class of the friction coefficient is given after rounding the results.

$$\mu = \sum_i P_i \cdot \mu_i \qquad (2)$$

On the example shown on figure 7, the graph of μ ahead is quite stable around 0.55, which is well corresponding to the road (gravel). But two degradations down to 0.3 (humidity) can be seen for the areas 5 (6m) and 8 (15m), they are corresponding to the parts with a high lighting. Here the systems thought it has seen wet parts of the road. Moreover, the maximal stability range is about 50 m in practice, which corresponds to the ranges bellow 12.

D. Time correlation of the measures

The confidence of the measure can be improved over the time by correlating the different measures. First the graph of μ needs to be transformed to give μ for all points ahead the vehicle. As the estimation is made only for regular areas on the picture, this graph will be constant steps with increasing size like on the figure bellow.



(a) Standard road on test tracks

(b) Corresponding instantaneous graph

Fig. 7. Example of two co-occurrence matrices

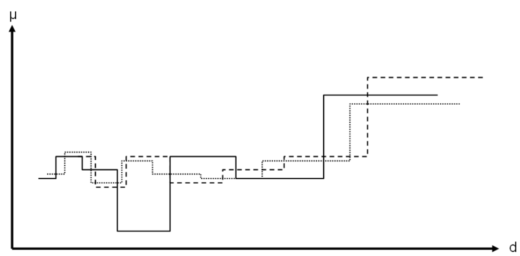


Fig. 8. Fusion of the predictive measures over the distance d ahead

Than the speed needs to be taken into account to match the new measures over the others like on the given figure. The range near to the vehicle will of course be the place with the most important number of measures. But all the measures have not the same confidence. Actually the first measures, which have been done as the vehicle was far from this point, are more roughly performed as the last ones. At 70 km/h about 50 measures can be matched on a same point for a visible analysis distance of 50 m.

That is why the fusion algorithm needs to take into account a weight for each measure depending on the time when this measurement was performed. Therefore the measures made for a same point are sorted in clusters, maximally one per μ classes. Than these clusters can be weighted to select the most important class. Finally for this class and the two neighbored classes the mean value is calculated taking into account once again the weights of the measures.

IV. Improvment of the reliability with a microphone

A. Needs of a reactive measurement

The predictive estimation can get some good results, but there can be somehow a need to estimate μ with another methodology, for example a reactive one. Indeed, critical systems need to have a redundancy of the sensing data to avoid failures due to problems with sensors or their algorithms for the analysis.

Therefore a reactive sensing method has been also integrated into the vehicle. This method is based on another analogy with the driver: the analysis of the sound coming from the road - tire contact. A small microphone (sampling rate mono 22050 kHz omni-directional) has been stuck on the fender of the front axle (at the opposite position of the motor) as shown on figure 9. At this position it can use optimally the loudspeaker effect [11] from the space between the road and the tire.

Fig. 9. Position of the microphone

B. Extraction of the characteristically frequencies

To extract the interesting frequencies from all this noise, the band of frequencies between 100 Hz and 650 Hz is grabbed with a dedicated microphone. The low frequencies have to be filtered to avoid the measurement of the motor noise [12] and the noise generated from vehicles near from the sensor. Therefore the analysis cannot be performed at low speed (in practice bellow 40 km/h) but in such cases the analysis can be avoided because of the lower interest of the results: ABS [13] [14] and traction control are for example disable for speed lower than 20 km/h.

As soon as the speed is high enough, some frequencies will grow up and generate the characteristically sound that the driver can hear too. Depending on the speed and on μ, there positions and amplitudes change and give the possibility to determine both speed and μ if enough frequencies are analyzed like on figure 10. Of course this analysis can be simplified if the speed is get from an external source.

The detection of the interesting frequencies is based first on a detection of the local maximum each 20 Hz. The curve fitting these points is after that modified by a low-pass filter (depicted on the same figure). From this filtering are extracted the most important local maximums, which are also on the same figure. Starting on the locations, the closest and highest peaks are sought in there ranges. Unfortunately the amplitude of these frequencies goes down quickly and this phenomena limits hence the number of frequencies, which can be monitored. In practice 3 frequencies have been analyzed permanently and sometimes two others can be monitored too.

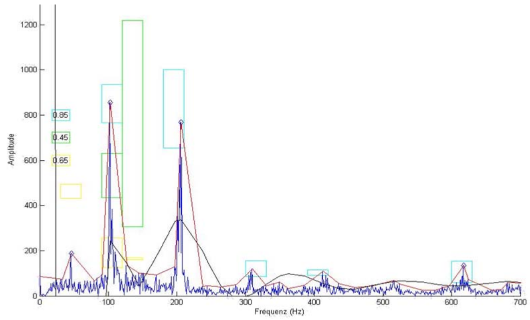


Fig. 10. Matching of the patterns at 70 km/h

C. Extraction of the model

First the peak corresponding to the sound of the motor (and especially the rounds per minute) has to be found from the list of potential interesting frequencies to define the speed. The figure 11 shows the position of this frequency ($\mathcal{F}$). After measures with the same speed but different rounds per minute (rpm), the following law has been established for the vehicle. This law is only acceptable is the speed is taken constant; as soon as the vehicle accelerates or brakes, this peaks will be moving. For the rest, the increasing of the speed has a unique effect to increase the perturbation noise as well.

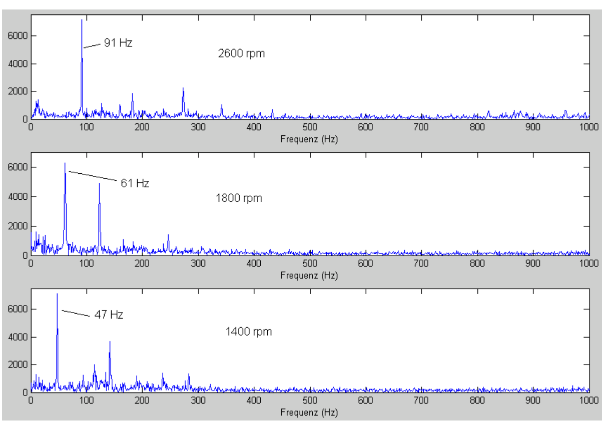


Fig. 11. Influence of the rpm for μ = 0.65

$$\mathcal{F} = 0.034 \cdot rpm + 1$$

The model is based also on several measures with different speeds and different friction coefficient like on figure 12. This model is constituted of many 30Hz wide rectangle, whom centre is placed at the calculated averages on the both axis and the height is equal to 3 times the variance of the amplitudes. The final results of the models can be shown on the figure 10.

D. Estimation of the μ coefficient

The amplitude of each frequency is analyzed separately to determine to which model it corresponds. This local method

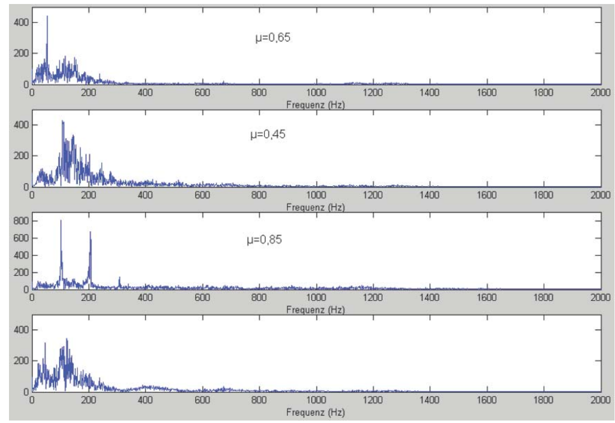


Fig. 12. Influence of μ at 70 km/h

has been chosen instead of any other global matching as the models can changed drastically from one vehicle to another. This method avoids the mathematical modeling of the ranges or a new learning phase of a neural network.

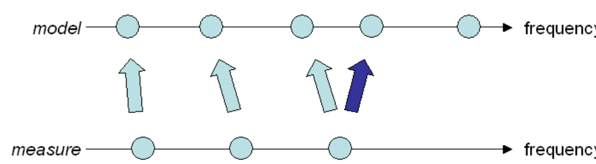


Fig. 13. Matching of extracted frequencies on a model

To do this, Gaussian curves are fit on the different ranges in the models. From the distance of the peak amplitude to the optimum of each range, the probability to corresponds to this class is implicitly given.

After that, for each class of μ, several probabilities are determined. The same approach for the fusion can be used as for the results coming from the camera by using the equations 1 and 2. But here the number of measures determined will change over the time, if the high frequencies are not extracted from the noise.

V. Integration of Reactive and Predictive Measures

In normal situation the checking algorithm is looking at the consistency of the results coming from both sources of measurement. The comparison of the results can be done only once the vehicle has reach the point of measure. As long as the measures are corresponding or the predictive data are a little bit lower than the reactive data, the predictive way of measurement gets the priority. Indeed if the μ is underestimated, the vehicle safety will not be in danger as the vehicle dynamics will be just reduced.

But if the predictive measures are bigger than the reactive ones, a dangerous conflict will appear. It may be

possible that a small road portion has been incorrectly analyzed if its surface is not wide enough. In such cases several types of textures have been matched together and the results tends to be estimated as a normal macadamized road ($\mu \approx 0.65$) as it can emphasis most kind of local textures. This phenomenon can also happen if their has been dirt (dust or water) on the windshield. In such cases temporal errors have no real impact on the vehicle safety as their range are not wide enough to destabilize the vehicle for example. Therefore a counter is integrated into the checking algorithm and it will switch off the predictive measurement only after a distance of 20 m.

VI. Conclusion and Future Works

A predictive method of measurement based on a camera has been presented here. The extraction of the textures and the gloss through the use of co-occurrence matrices, permits to estimate μ with 6 different classes. Over the time an auto-correlation improves the reliability of the estimation by detecting inconsistencies. But the blur depending on the speed is not well taken into account and needs more investigation because of its impact on the picture.

After that, a reactive method based on a microphone extracts characteristically frequencies and matches them on models. These patterns are depending on the vehicles and the tires. This method must be calibrated with a generic tire model. But it can deliver a measure of μ and not just an estimation. Furthermore, the life cycle of such devices may be too short for automotive industry as they are integrated where all the dust coming from the road is binding itself on the vehicle shield.

References

[1] J. Wang, P. Agrawal, L. Alexander, and R. Rajamani, "An experimental study wiht alternate measurement systems for estimation of tire road friction coefficient," *American Control Conference*, pp. 4957–4962, June 2003.

[2] J.-O. Hahn, R. Rajamani, and L. Alexander, "Gps-based real-time identification of tire-road friction coefficient," in *IEEE Transactions on Control Systems Technology*, vol. 10, pp. 331–343, May 2002.

[3] F. Gustavson, "Slip-based estimation of tire-road friction," Linkping University, Sweden, 1995.

[4] T. Kuno and H. Sugiura, "Detection of road conditions with ccd cameras mounted on a vehicle," in *Systems and Computers in Japan*, vol. 30, pp. 88–99, 1999.

[5] M. Bellino, Y. L. de Meneses, P. Ryser, and J. Jacot, "Lane detection algorithm for an onboard camera," *SPIE proceedings of the first Workshop on Photonics in the Automobile*, 2004.

[6] A. Broggi, M. Bertozzi, A. Fascioli, C. G. lo Bianco, and A. Piazzi, "The argo autonomous vehicles vision and control systems," in *International Journal of Intelligent Control and Systems*, vol. 3, pp. 409–441, 1999.

[7] A. Laine and J. Fan, "Texture classification by wavelet packet signatures," Tech. Rep. IRI-9111375, National Science Fundation, 1991.

[8] A. Baraldi and F. Parmiggiani, "An investigation of the textural characteristics associated with gray level cooccurrence matrix statistical parameters," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 33, pp. 293–304, March 1995.

[9] J. R. Carr and F. P. D. Miranda, "The semivariogram in comparison to the co-occurrence matrix for classification of image texture," *IEEE Transactions on Geoscience and Remote Sensing*, 1998.

[10] M. Partio, B. Cramariuc, M. Gabbouj, and A. Visa, "Rock texture retrieval using gray level co-occurrence matrix," 2002.

[11] P. M. Nelson and S. M. Phillips, "Quieter road surfaces," tech. rep., TRL Limited, 1997.

[12] H. Wu, M. Siegel, and P. Khosla, "Vehicle sound signature recognition by frequency vector principal component analysis," in *IEEE Transactions on Instrumentation and Measurement*, vol. 48, pp. 1005–1009, 1999.

[13] C. Ünsal and P. Kachroo, "Sliding mode measurement feedback control for antilock braking systems," *IEEE Transactions on Control Systems Technology*, March 1999.

[14] I. Petersen, T. A. Johansen, J. Kalkkuhl, and J. Ldemann, "Wheel slip control in abs brakes using gain scheduled constrained lqr," *Proceedings of European Control Conference*, 2001.